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Dynamic alignment control using depth imagery for automated wheel assembly

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Abstract

This paper presents a novel method for dynamic alignment control using infrared light depth imagery to enable automated wheel loading operation for the trim and final automotive assembly line. A key requirement for automated wheel loading is to track the motion of the wheel hub and simultaneously identify the spatial positions and angular orientations of its alignment features in real-time on a moving vehicle body. This requirement is met in this work, where low-cost infrared depth-imaging devices like Microsoft Kinect™ and Asus Xtion™, vastly popular in the gaming industry, are used to track a moving wheel hub and recognise alignment features on both the wheel hub and the wheel in real time in a laboratory environment. Accurate control instructions are then computed to instruct the automation system to rotate the wheel to achieve precise alignment with the wheel hub and load the wheel at the right time. Experimental results demonstrate that the reproducibility error in alignment control satisfies the assembly tolerance of 2mm for the wheel loading operation, and thus the proposed method can be applied to automate wheel assembly on the trim and final automotive assembly line. The novelty of this work lies in its use of depth imaging for dynamic alignment control, which provides real-time spatial data in all 3 axes simultaneously as against the popularly reported RGB imaging techniques that are computationally more demanding, sensitive to ambient lighting and require the use of additional force sensors to obtain depth axis control data. This paper demonstrates the concept of a light-controlled factory where depth imaging using infrared light and depth image analysis is used to enable intelligent control in automation.

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Keywords: Dynamic wheel alignment; wheel loading; light-controlled automation; depth imaging; object recognition; Kinect; Xtion.

1. Introduction

Over the past 3 decades, automation has played a key role in enhancing the productivity and product quality of the global automotive manufacturing industry. While body construction and paint shops are automated, the trim and final assembly line, where the vehicle gets its instrumentation, seats, doors, trims, and wheels among other things, is the least automated [1, 2]. This is because it is not possible to use pre-programmed industrial robots to assemble parts on a constantly moving vehicle body. The conveyor line, on which the vehicle body is mounted, moves constantly at a typical rate of 100mm/s with arbitrary deviations in motion [3]. Preliminary analysis of conveyor dynamic motion has already been reported [4]. However, to maintain global competitiveness, automotive manufacturing companies are now feeling the need to automate trim and final assembly lines [1].

One example of manual operation in the trim and final assembly line is wheel loading. In this operation, the operator grabs a new wheel, tracks the movement of the vehicle body on the conveyor to anticipate loading instance and position, loads the wheel on the wheel hub of the vehicle, fastens the bolts and pulls back in a typical time period of 10 seconds [5]. Wheel loading is among the first targets for automation

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because of the high manpower costs associated with it [6]. The advent of musculoskeletal disorders in operators, caused by manoeuvring heavy wheels in uncomfortable body postures during installation despite using weight compensation gantries (see Fig. 1.), has further reinforced the need for automation.

Human operators perform wheel loading accurately and effectively using their multi-modal sensing abilities and skills acquired by training and experience. These characteristics allow them to intelligently manoeuver the wheel towards the wheel hub and install it while constantly compensating for arbitrary motion deviations of the vehicle body. They have to instinctively rotate the wheel if required to align the tapped bores on the wheel to the threaded studs on the wheel hub and swiftly react to take adaptive steps in case of unforeseen situations like unplanned conveyor halts. Therefore, it has been difficult to replace skilled human wheel loading operators with automated solutions.

Fig. 1. Manual wheel loading operation [7].

In this article, the authors have proposed a unique solution for dynamic alignment control to enable automated wheel loading. The proposed system uses robust, low-cost depth imaging devices like Microsoft Kinect™ and Asus Xtion™ to simultaneously capture depth images of the wheel and the moving wheel hub. These images are processed in real time to minimise noise and accurately recognise and track relevant features in those objects in order to determine the most effective alignment manoeuver. Because of low implementation costs, high portability and multi-dimensional tracking capability, the approach used in this work has the potential to enable automation of not only wheel loading but also other 'assembly-in-motion' operations.

2. Related Work

A few researchers have attempted to automate the manual wheel loading operation. In all these solutions, the human skills of aligning the wheel with the wheel hub and gauging the speed of the vehicle body on the conveyor to anticipate wheel loading instance and position are replaced by automation solutions aided by vision systems and force sensors.

Cho et al. have proposed the use of a macro-micro visual tracking manipulator using a camera on the wheel gripper mounted on an industrial robot to track the centre of the wheel hub [5]. The method of aligning the wheel to the wheel hub is not reported. The macro part of the conveyor tracking system of the robot tracks the velocity of the moving hub flange, while the micro part tracks the fine position error measured by the camera to assist in wheel loading. Chen et al. have used a combination of visual servoing to track the motion of the vehicle body in two axes to determine the wheel-loading instance and position [6]. Force sensors along all 3 axes are used to control the motion of the robot towards the wheel hub to perform loading according to set values of compliant contact forces between the robot tool and the wheel hub. Alignment is achieved by computing the transformation required to rotate the tool, holding the wheel, to match the wheel hub orientation recognised by the vision system. Shi and Menassa have proposed a coarse vision system to track the macro motion of the moving vehicle body, a fine vision system to track the small deviations in vehicle body motion and an end-of-arm tool with a vision camera to locate the wheel hub studs for alignment [1]. Lange et al. have proposed coarse and fine sensing systems and a compliant force-torque sensor in the end-effector to control the loading step to compensate for small-scale oscillations of the wheel hub [3]. Predictive modelling of robot motion trajectory control in addition to the computed trajectories based on sensor inputs is also proposed to enhance the accuracy of wheel loading [8]. For alignment, the camera on the end-effector tracks the centre of the wheel hub and identifies the positions of the studs to determine its orientation.

In all the above articles, researchers have used stereo or Charge-Coupled Device (CCD) camera based vision systems to track and identify relevant features on the wheel and the wheel hub and therefore are computationally intensive due to real time image processing and are expensive to implement. Secondly, because of their use of Red-Green-Blue (RGB) data, ambient light conditions in which the objects are tracked may affect image-processing accuracy. Thirdly, vision systems can only effectively provide motion information of an object along two axes and additional force sensors are required to provide the same along the third axis.

In this work, inexpensive depth imaging devices and depth-based object recognition methods are used to obtain motion information along all 3 axes. Depth data is also used to recognise and track features belonging to moving objects. Since depth data is provided by Infra-Red (IR) and not visible light (RGB) imaging, the proposed technique does not depend on ambient light conditions. Though, the devices used in this work are largely used to capture human motion for gaming applications, their capabilities have been extended to track moving objects and recognise and characterise features in those moving objects in the context of manufacturing automation.

3. Method

3.1. Experimental Setup

The components of this experiment are:

a) One wheel with a central bore and four tapped bores along a pitch centre diameter (PCD) of 108mm (Figure 5a).

b) One wheel hub with a central bore and four threaded studs along a PCD of 108mm (Figure 6a).
c) One Microsoft Xbox Kinect™, hereinafter called ‘Kinect’ mounted on a tripod.
d) One Asus Xtion™ Pro Live, hereinafter called ‘Xtion’ mounted on a tripod.
e) One Comau NM-45 industrial robot arm to emulate the automotive conveyor line.

A depth-imaging device provides depth data in millimeters of all the pixels belonging to exposed surfaces in the 3-Dimensional (3D) scene in front of it. Two different depth-imaging devices, Kinect and Xtion are used in this work. The Xtion is placed 1m away from the stationary wheel and facing the rear side of the wheel. This view is chosen because in a real automation scenario it would be the only side available for the Xtion to view with the front side of the wheel being gripped by the loading robot tool. The height and tilt of the Xtion is adjusted to roughly align its view with the centre of the wheel (see Fig. 2).

Fig. 2. Using Xtion to capture the wheel parameters.

The Kinect is placed at a distance of 1m from the wheel hub and facing the robot arm that is holding the wheel hub. Its height and tilt is adjusted to roughly align its view with the centre of the wheel hub (see Fig. 3).

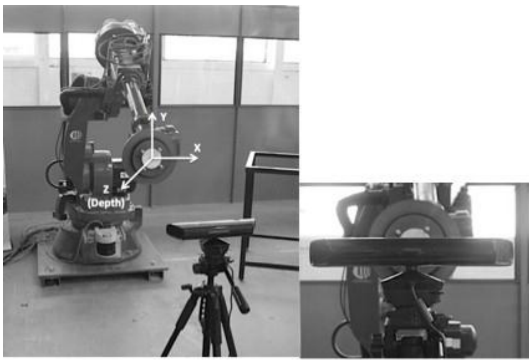


Fig. 3. Using Kinect to capture the wheel hub parameters.

The wheel hub is mounted on the end-effector of the robot arm using a central disc with the threaded shaft of the wheel hub studs facing outside and towards the Kinect (see Fig. 4).

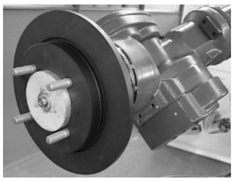


Fig. 4. Robot arm end-effector holding the wheel hub.

The robot arm is used to emulate the motion of the wheel hub mounted on the vehicle on a moving conveyor line. The vertical position of the robot arm end-effector is adjusted to be within the central view of the Kinect. The robot arm is programmed to move in a straight line along X-axis for a distance of 2m at an average speed of about 100mm/s. The speed changes constantly as the robot arm accelerates from the starting point to 120mm/s and decelerates towards the ending point. These changes in speed imitate the deviations in speed of an actual conveyor line though the nature of deviations is not the same.

A Java-based software development platform called ‘Processing’ was used to write the object tracking and feature recognition code. The depth imaging functions from ‘SimpleOpenNI’, an open source library to interface with both Kinect and Xtion, were used. The code was executed on the Mac OS X operating system.

3.2. Sequence of events

This experiment emulates the actual moving wheel loading environment and simplifies it. The sequence of events during this experiment is as follows:

a) The Xtion captures a series of the depth image frames of the stationary wheel. For each image frame, the features of the wheel, like the circumference, centre and the angular orientation of the four tapped bores are identified.
b) The robot arm moves the wheel hub linearly across the Kinect for a distance of 2m at an average speed of 100mm/s.
c) At the same time as step b, the Kinect captures a series of the depth image frames of the moving wheel hub. For each image frame, the features of the wheel hub, like the circumference, centre and the angular orientation of the four studs are identified.
d) The difference between angular orientations of the wheel bores and the wheel hub studs is computed and the most optimal alignment manoeuver to align the wheel with the wheel hub is determined to aid in automated loading.

3.3. Object tracking and feature recognition of the stationary wheel

The depth images of the stationary wheel are generated by the Xtion (see stationary wheel drawing in Fig. 5a.). By analyzing each image frame (see Fig. 5b.), it is determined that the depth values of pixels within the hollow central bore area are deeper than the pixels on the surrounding rim surface.

Obtaining the minimum and maximum X and Y values within this area and calculating the midpoints, the wheel centre is obtained.

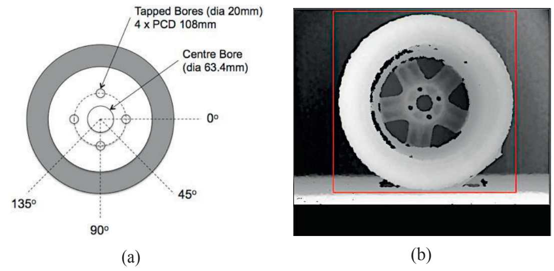


Fig. 5. (a) Wheel drawing; (b) Depth image of the wheel.

A similar technique is used to identify the four hollow tapped bores of the wheel by determining the angular boundaries of pixels belonging to them and obtaining the centre points. Though all four bores are identified, the angular position of the tapped bore located in the 45° to 135° quadrant is recorded. This quadrant is chosen because it presents the most satisfactory quality of feature rendering within all the depth images across multiple experiments.

3.4. Object tracking and feature recognition of the moving wheel hub

The depth images of the moving wheel hub (see drawing of the moving wheel hub in Fig. 6a. and depth image in Fig. 6b.) are generated by the Kinect.

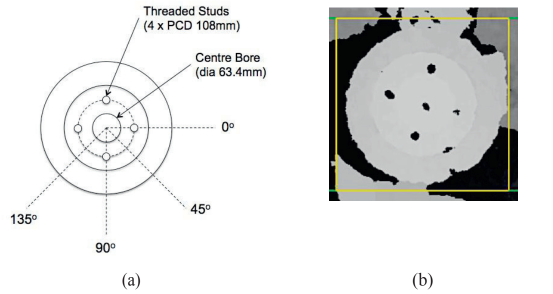


Fig. 6. (a) Wheel hub drawing; (b) Depth image of the wheel hub.

When the wheel hub comes within the 0.8m long motion tracking zone (see Fig. 7a.), the depth values of the closest object to the Kinect, are compared against the background to determine the circumference of the wheel hub. This circumference is tracked throughout its motion within the zone, and its speed is computed every second and recorded. Once the wheel hub enters the 0.4m long feature recognition zone, the angular boundaries of pixels belonging to the four studs and their centre points are obtained (see Fig. 7b.). The pixels belonging to the studs are identifiable because their depth values are lower than those of the surrounding hub surface. Subsequently, the angular position of the stud located in the 45° to 135° quadrant is recorded.

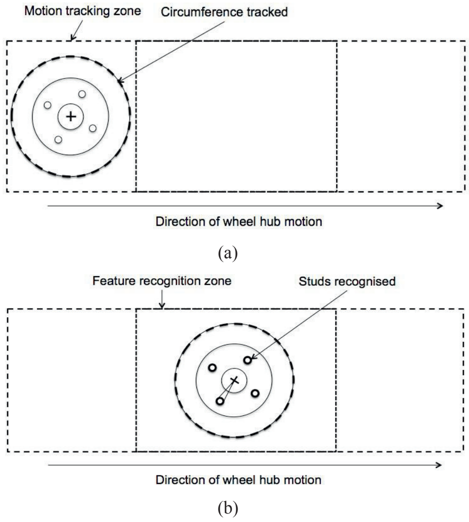


Fig. 7. (a) Identification of wheel hub; (b) Recognition of threaded studs.

3.5. Determination of optimum alignment manoeuver

The difference between the recorded angular orientations of the wheel bore and the wheel hub stud, located within the 45° to 135° quadrant, represents the misalignment between the two objects (see Fig. 8). In order to align the two objects, either of them could be rotated to match the angular feature orientation of the other. However, as per the application scenario on the trim and final vehicle assembly line, only the wheel can be rotated. It is evident from Fig. 8., that the wheel can either be rotated clockwise or counter-clockwise thereby providing two possible alignment manoeuvres. The system then computes the rotation angles for the two choices and selects the least rotation angle for alignment.

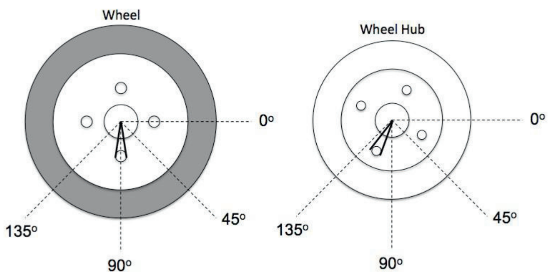


Fig. 8. Misalignment of wheel and wheel hub features.

3.6. Improvement in alignment accuracy

The depth images produced by both Kinect and Xtion are noisy in real time. The depth values produced at the rate of 30 frames per second (fps) are not completely consistent across frames even for stationary objects. Therefore, performing feature recognition using only one depth image frame will not be accurate. In this work, an the angular positions of the alignment features computed in the current depth image frame are cumulatively averaged with those of the previous image frame to reduce overall error over the tracking period. The optimum number of frames to be used in the averaging technique is investigated. Feature recognition suffers from degradation of accuracy when the moving object is at the periphery of the depth imaging field of view. Therefore, feature recognition is only carried out when the moving object is in the central zone where depth imaging is reliable and accurate.

4. Results

4.1. Object tracking and feature recognition of the stationary wheel

Upon detection of the stationary wheel, the depth images provided by the Xtion are analysed. The centre point of the central bore is located and the circumference is computed and displayed. The angular position of the first tapped bore within the 45° to 135° quadrant is located and recorded. Subsequently, the 3 other bores along the PCD are identified and displayed on screen to complete the feature recognition of the wheel (see Fig. 9.).

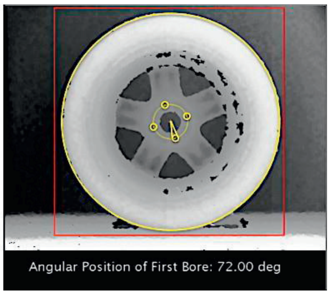


Fig. 9. Object and feature recognition of the wheel.

4.2. Object tracking and feature recognition of the moving wheel hub with determination of alignment manoeuver

Upon detection of the wheel hub within the motion-tracking zone, the depth images provided by the Kinect are analysed. The circumference of the wheel hub is determined and the centre point is computed and displayed. By continuously tracking the circumference, the speed at which the wheel hub moves is computed and recorded after every 30 frames.

Upon detection of the wheel hub in the feature recognition zone, the angular position of the first stud within the 45° to 135° quadrant and the 3 other studs along the PCD are identified and displayed. The wheel bore positions are also superimposed on the depth image. At this stage, the difference between the angular positions of the first wheel hub stud and the first wheel bore is computed and the optimum alignment manoeuver is determined and displayed (see Fig. 10a and 10b.).

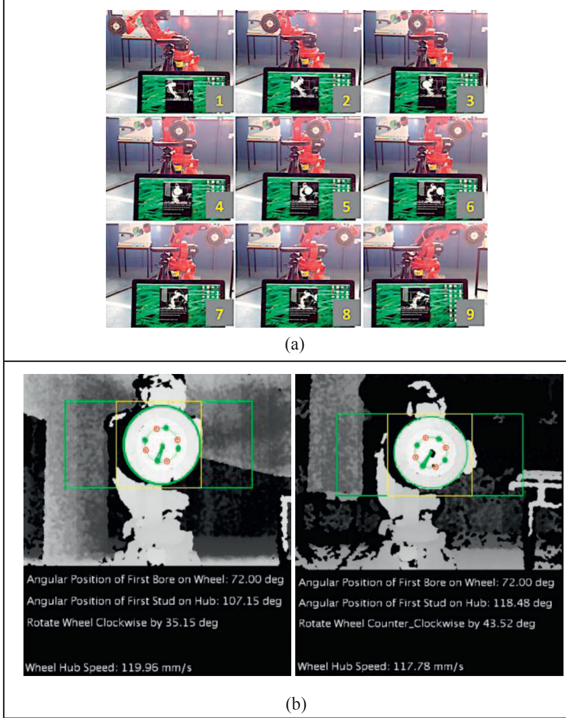


Fig. 10. (a) Video grabs of moving wheel hub; (b) tracked speed and optimum alignment manoeuvre displayed.

4.3. Improvement in alignment accuracy

In this work, alignment accuracy is measured with respect to the reproducibility of angular feature positions across multiple iterations of the experiment and not by comparing them with actual or nominal values. As long as the radial positioning error, resulting from the maximum standard deviation in angular feature positions of both the wheel and the wheel hub, is below the industry requirement, the reported alignment accuracy is adequate for automation.

The angular feature positions determined in each image frame are cumulatively averaged with those determined from the previous image frame, reducing mean error with each subsequent frame. The averaging was done over 1 - no averaging, 30, 60, 90 and 120 frames. The robot motion speed was reduced to an average of 60mm/s to accommodate the extra time required for averaging over 120 frames. Since both the depth cameras operate at 30fps, the time taken for feature detection varied from 1 second for no averaging to 4 seconds for averaging 120 frames. The mean angular feature positions at the end of the averaging process and their standard deviations (see Table 1.).

Table 1. Results from experiment runs with varying number of averaged frames.

Iteration	Stationary Wheel (Angular Position of First Bore)					Moving Wheel Hub (Angular Position of First Stud)				
	No of Frames Averaged					No of Frames Averaged				
	1	30	60	90	120	1	30	60	90	120
1	73.00	72.21	72.58	72.70	72.00	105.97	109.04	108.26	108.50	108.19
2	72.00	72.00	72.54	72.10	72.07	116.88	99.35	105.45	108.67	109.79
3	72.19	72.94	72.07	72.23	72.57	87.74	107.05	107.44	106.59	109.67
4	72.98	72.80	72.21	72.12	72.10	96.62	105.36	104.58	108.43	108.05
5	72.10	73.01	72.01	71.95	72.20	106.88	104.66	104.33	109.66	108.23
6	74.00	73.70	72.25	72.04	72.53	96.70	108.66	107.15	108.80	105.83
7	73.56	72.99	72.38	72.00	72.06	96.59	99.72	108.78	106.30	106.11
8	73.00	72.24	72.78	72.00	71.99	108.71	108.97	105.01	107.15	108.87
9	72.13	72.07	72.98	72.29	72.12	107.89	107.56	109.04	109.63	108.30
10	71.00	72.80	72.78	72.00	72.49	110.39	106.28	108.01	106.14	109.91
Mean	**72.60**	**72.80**	**72.46**	**72.14**	**72.21**	**103.44**	**105.67**	**106.81**	**107.99**	**108.30**
Std. Dev.	**0.88**	**0.57**	**0.33**	**0.22**	**0.23**	**8.69**	**3.55**	**1.80**	**1.33**	**1.41**

5. Discussion

5.1. Impact of distance between depth imaging device and the object

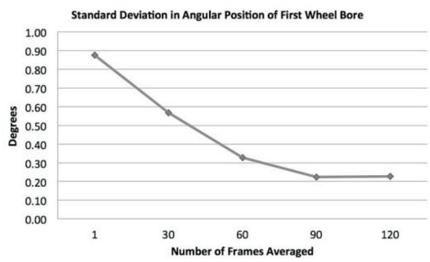
In both the wheel and wheel hub tracking experiments, the depth imaging devices are placed at a distance of 1m from the objects. This distance enables the depth imaging devices to clearly capture the object features. This is also in accordance to the Kinect characterisation study [9], which reports that for accurate object mapping, the data should be acquired within 1 and 3m distance from the device. At larger distances, the quality of the data is degraded by noise and low resolution of the depth measurements. At shorter distances, depth information of some surfaces of the object may not be available and therefore not rendered in the depth image. However, at a 1m distance the field of view of the depth imaging device is limited to 0.8m whereas the wheel loading assembly workstation is about 2m in length. Therefore, to continuously monitor the motion of the moving vehicle body before the instance of wheel loading for about 1.2 to 1.5m, at least 2 depth imaging devices with merged fields of view and motion tracking zones are required.

5.2. Impact of number of image frames used for averaging

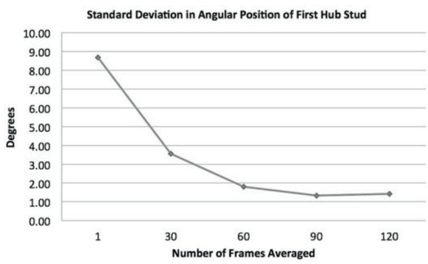
It can be noted that the standard deviation of angular feature position results decreases as the number of frames averaged increases (see Fig. 11a. and 11b.). However, as the number of frames increases, the time required for feature recognition also increases. The typical wheel loading duration in the trim and final automotive assembly line industry is 10 seconds. Therefore, the time of 3 seconds taken for averaging 90 frames is regarded acceptable especially when the difference in standard deviation between averaging 90 frames and averaging 120 frames is not significant. It can also be noted that the standard deviation values are higher for the wheel hub, due to the smaller dimensions of its features and that feature recognition is performed on the moving wheel hub, against the values achieved with the stationary wheel.

In order to successfully load the wheel on the vehicle, all the four tapped bores on the wheel must go through the corresponding four studs of the wheel hub without touching them. In this work, the diameter of the wheel bores is 20mm and that of the studs is 12mm. Therefore, the tolerance for loading is 4mm on either side of the centre of the tapped bore. This value can go down to 2mm for some vehicle models in the automotive industry.

The resultant standard deviation of 1.33^{o} (90 frames averaged) obtained for the wheel hub is equivalent to 1.26mm in radial positioning error from the centre of the wheel bore. This error value is lower than the minimum industry requirement of 2mm.



(a)



(b)

Fig. 11. Standard deviation in results for (a) wheel and (b) wheel hub.

5.3. Use of depth imaging as an automation aid

From the previous sections, it can be seen how depth imaging can be used to track stationary and moving objects and recognise their features. The spatial positions and angular orientations of those features can be recorded and used to enable automated solutions that manipulate those objects.

In the case of actual automated wheel loading (see Fig. 12.), recognition of the wheel hub in the motion tracking zone can detect the presence of the vehicle body on the conveyor line moving towards the wheel-loading workstation to trigger the wheel loading robot to pick up the wheel, align it and load it on the wheel hub.

By tracking the moving wheel hub using one or more stationary depth imaging devices, the speed at which the vehicle body moves on the conveyor line along with its motion deviations in all 3 axes can be tracked. By knowing the speed and the motion deviations of the moving wheel hub, and mapping the spatial coordinate system of the stationary depth imaging device with that of the wheel loading robot arm, the wheel loading instance and position relative to the robot arm can be determined (not in the scope of this paper).

While the moving hub is being tracked, the wheel loading robot arm picks the wheel and manoeuvres it in front of another stationary depth imaging device to identify the alignment features on the wheel. The alignment control program would then compute the difference in alignment between the wheel hub and the wheel and command the robot arm end-effector to rotate the wheel accordingly before loading. The same method is applied for rear wheel loading.

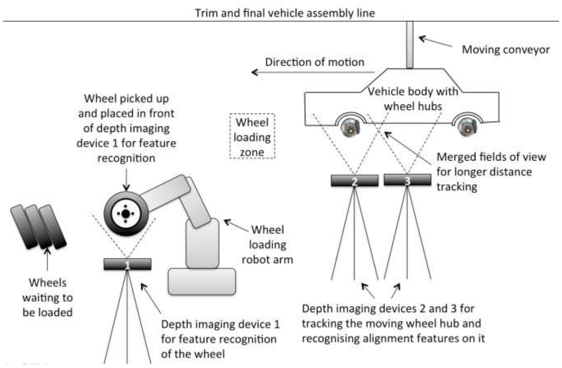


Fig. 12. Illustration of a conceivable automated wheel loading station.

Depth imaging technologies, that use IR light as the imaging medium, can therefore be used to provide automation solutions, in this case to replace the currently manual wheel loading operation in the trim and final automotive assembly line.

5.4. Future Work

To accurately determine the wheel loading instance and position, it is necessary to track the motion deviations of the wheel hub not only in the direction of motion (x-axis) but also in the y and z-axis to counter for the sway in the vehicle body during its motion on the conveyor line.

Currently, the motion tracking zone and feature recognition zone are 0.8m and 0.4m respectively based on the constraint of a limited field of view offered by the depth imaging devices and the short distances they are placed away from the objects (1m). These zone lengths are not sufficient to handle situations when the conveyor line suddenly stops or abruptly changes motion speed. Therefore, multiple depth imaging devices with merged field of views will need to be used to track the moving wheel hub to cover the entire line distance from the previous assembly workstation to the wheel-loading workstation.

The disc brakes fitted on the wheel hub of the actual vehicle would have the brake calipers mounted on them already before the wheel loading operation. Therefore, the tracking method proposed here will need to be amended to recognise the circumference of the wheel hub in the presence of the brake caliper.

Depth imaging has the potential to cater to the above issues that will be investigated in future work.

6. Conclusion

In this paper, a method for dynamic alignment of the wheel and wheel hub is developed and presented. It is dynamic because the wheel hub is constantly moving while the proposed method makes alignment control decisions. This work successfully demonstrates how human skill associated with wheel loading, such as real time alignment of objects can be potentially replaced by automation solutions aided by depth imagery. The novelty of this work lies in its use of low-cost depth imaging devices for dynamic alignment control, providing real-time spatial data in all 3 axes simultaneously as against the popularly reported RGB imaging techniques. Experiments were also performed to enhance the reproducibility of feature recognition using an averaging technique and results showed that the mean radial positioning errors were lower than the minimum assembly tolerance required for wheel loading in the automotive industry. This paper demonstrates the concept of a light-controlled factory where optical measurement using infrared light and depth imaging is used to aid automation. The proposed method has the potential to enable not only the automated wheel loading operation but also the automation of most assemblies in motion thereby having a significant impact on improving the efficiencies and productivities of global automotive manufacturing companies.

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